EVALUATION OF DEMAND PREDICTION TECHNIQUES

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Executive Summary

EVALUATION OF DEMAND PREDICTION TECHNIQUES

Reparable spares of aircraft components constitute an important management item for the Air Force, amounting to a computed budget requirement of $4.077 billion in FY85.

Allocation of this investment across items is critical to the readiness and sustainability of weapon systems. Proper allocation, in turn, depends on solving the statistical problem of estimating item demand rates and variances.

Using historical Air Force data, we have compared the performance of various estimating procedures, including the one used in the Air Force Recoverable Consumption Item Requirements (D041) system, which computes item Peacetime Operating Stock (POS) requirements. To be consistent with Air Force orientation toward weapon system management, aircraft availability, an aspect of readiness, served as the measure of performance.

Our major conclusions:

- For estimating demand rates, exponential smoothing techniques are superior to today's D041 moving-average rates and are, in fact, the best techniques of those we studied.
- Use of a Poisson or constant variance-to-mean ratio (VMR) leads to poor allocation of resources. Treating the VMR as a power function of the mean demand rate is preferable.

Incorporating these techniques into the D041 computation would be a simple matter, and the Air Force would benefit significantly. When compared to current AFLC policy, the proposed techniques showed a reduction in backorders of over 50 percent for the F-16 and the A-10 weapon systems.

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CHAPTER 1

INTRODUCTION

Reparable items constitute an important management problem for the Air Force. In FY85, the computed budget requirement for these items was $4.077 billion, and allocation of this investment across items has a critical effect on the availability of weapon systems.

Few studies of demand prediction pertaining specifically to the Air Force have been conducted in recent years. The Stevens and Hill [1] study is the basis for much of Air Force's present policy. A recent study, Sherbrooke [2], estimated that exponential smoothing with a constant of .4 applied to quarterly data could produce a 39-percent reduction in squared error and a 12-percent reduction in average absolute error over the 8-quarter moving average now in use. A modification of the equation for predicting the variance-to-mean ratio (VMR) was also proposed.

The weapon system approach of the present study distinguishes it from earlier ones. The data in Sherbrooke [2] came from a stratified random sample of 1,027 items from the Air Force inventory. With the data on all reparable items for each of several weapon systems, it is possible for availability to serve as the measure of performance. This is more meaningful than such measures as squared error or average absolute error, because availability is the Air Force's objective when it allocates funds to spare parts.

Another reason to perform this study was to see whether the recommendations for predicting demand were consistent across several weapon systems. If the recommendations varied between one weapon system and another, their utility and validity would be questionable. Moreover, though quarterly Recoverable Consumption Item Requirements (D041) data serve as the primary source, as in the earlier study, it was important to obtain some transaction data from an individual base. This information yields the interval between demands – not quarterly summaries – and thus tells us more about the "physics" of the demand process.

Section 2 describes the demand prediction experiment, beginning with definitions of several candidate techniques for predicting mean demand and the VMR. We

discuss the availability criterion, the data provided by the D041 system, and the prediction process for each technique (a "technique" being defined as a process for predicting the mean demand and the VMR). Finally, we describe the evaluation procedure and compare the performance of the various techniques.

Chapter 3 presents the results, Chapter 4 the major conclusions. Detailed results are reported in the appendices.

CHAPTER 2

DESCRIPTION OF THE EXPERIMENT

The objectives of this study are to find demand prediction techniques that: (1) *achieve* a high level of system availability in the future and (2) *predict* a level of system availability similar to the level achieved.

The candidate procedures for predicting mean demand fall into the four categories shown in Table 2-1. Let M be the predicted mean demand, D(1) the demand in the most recent quarter, D(2) the demand in the preceding quarter, etc. For exponential smoothing, an example is shown where the smoothing constant, A, is set at .4. (In Sherbrooke [2] a value of .4 on quarterly data appeared best.) The Air Force now uses the second procedure, a moving average, with $N = 8$. This weights each of the last 8 quarters equally and gives no weight to earlier quarters.

The Bayesian procedure is the "objective Bayes" technique that was applied at George Air Force Base in 1965 and documented in Feeney and Sherbrooke [3]. The basic idea is that the two parameters of a single gamma prior probability distribution are estimated from past demand on all items. Bayes theorem is then used to combine this prior distribution with specific data about an item to obtain posterior distributions that will differ by item. The important difference between the Bayes procedure and the two previous procedures is that the Bayesian approach yields a probability distribution – instead of a point estimate – of demand. There is, therefore, no need to develop a variance-estimating procedure for the Bayes technique.

Finally, it is possible to use higher-order procedures where both a trend and a mean value are estimated. We followed a procedure called "Holt linear estimation," which is described in Makridakis and Hibon [4]; it consists basically of second-order exponential smoothing. The first parameter is the same as the first-order exponential smoothing parameter and is set at .4, as above. The second parameter is a trend value that we set at .5 after some trial and error. However, we restricted the rate of growth for trend to eliminate absurd inferences or estimates of negative demand. For example, the absolute value of the trend/quarter was limited to

15 percent of the mean value, so that over 4 periods the mean could increase or decrease by 60 percent at most.

TABLE 2-1

PROCEDURES FOR PREDICTING MEAN DEMAND

1. Exponential smoothing

   $M = AD(1) + A(1-A)D(2) + A(1-A)^2 D(3) \ldots$

   Example: $A = .4$

   $M = .4D(1) + .24D(2) + .144D(3) \ldots$

2. Moving average

   $M = (D(1) + D(2) \ldots + D(N))/N$

   Example: $N = 8$

   Prediction $= .125D(1) + .125D(2) \ldots + .125D(8)$

3. Bayes

   Prediction is a combination of observed demand and the prior probability distribution

   Estimate of variance provided

4. Higher-order procedures with trend also estimated

The earlier work for Air Force Logistics Command (AFLC) in Sherbrooke [2] made it clear that it is important to estimate the VMR as well as the mean. Four types of candidate procedures are considered in Table 2-2. The first is a power relation, where the VMR is an increasing function of the mean. Here the mean is expressed as an annual value. If the mean is expressed over any other time period, the exponent is unchanged, but the multiplicative constant is altered. The expression shown here is very similar to the expression derived in the earlier AFLC study and does well in this experiment, too. Note that the independent variable, the mean, is not measured over the repair time. That would understate observed variability, because variability is caused not by the duration of repair time, but the drift in the mean value over time. We shall return to this subject.

TABLE 2-2

PROCEDURES FOR PREDICTING VARIANCE

1. Power relations
Example: $VMR = 1 + .14M^{.5}$
2. Based on sample variance from past data
3. Bayesian
4. Combinations of Techniques 1, 2, and 3

Another procedure is to estimate the item variance from the variance computed from the earlier data (or from the mean absolute deviation, as in exponential smoothing). A third type of procedure is the Bayesian, which automatically provides an estimate of variance. Finally, recent research, as in Winkler and Makridakis [5], suggests that combinations of procedures may outperform individual procedures. In our application, a general power relation, such as Procedure 1, in combination with a Procedure 2 that is sensitive to extreme variation in the history of an item, may outperform either procedure alone.

A major difference between this study and earlier studies of demand is the evaluation mechanism. Most prediction studies use some model-independent measure to evaluate accuracy. The problem is that there are many candidates, and it is hard to decide which, if any, is appropriate. Average absolute error is a common measure, but should the error on a very-high-demand item be divided by some factor before adding it to the error on a low-demand item? Should the same error on two items that are widely different in unit costs be weighted equally? If the error is twice as large, should the penalty be twice as heavy – or should it be heavier, as in a squared-error criterion? Is it reasonable to assign as much weight to an overprediction error as to an underprediction error? Many economic studies use percentage error, but many of our items have a "true demand" of zero. This causes problems as a divisor.

Our view is that end-item availability should be used, because the objective of demand prediction on a group of items is to maximize availability for a specified budget. Availability is easily calculated, as shown in the formula in Table 2-3. We need to compute the expected backorders (EBOs) for a given item and divide by the number of end items, N (e.g., aircraft). Subtracting from 1 gives the expected fraction of the fleet that is not down for lack of that item (under the assumptions that backorders are randomly distributed across aircraft and the number of backorders for any items is small compared with the size of the fleet). Multiplying by a similar expression for every item gives the fraction of the fleet that is available.

TABLE 2-3

EVALUATION OF TECHNIQUES

Model-independent measures
Average absolute error
Mean-squared error
Percentage error
Model-dependent measure
Availability = $[1 - EBO(1)/N]\,[1 - EBO(2)/N]\ldots$

The data for this demand prediction experiment were taken from 16 quarters of D041 data. We drew on the first 12 quarters for historical data and used the last 4 quarters to evaluate accuracy of prediction. C-5s were selected because they operate from only two home bases. Worldwide demand, as drawn from the D041, is therefore not too different from base-level demand, although demands do occur at other en route bases during flight. The data used in the calculations are listed in Table 2-4: base-level demand by quarter, unit cost, not-reparable-this-station (NRTS) demand (which goes to depot), and average base and depot repair times by item. All nonengine, first-indenture items (line replaceable units) with some demand – there were 560 such items – were used.

Data from the C-5 engine, A-10 airframe, and the F-16 engine/airframe were also used in further tests. These tests are described in Appendices A through E. The

average repair time by item is the sum of: (1) the base repair time multiplied by (1 – NRTS) and (2) the order-and-ship time plus the average depot delay caused by not having an item on the shelf, multiplied by the NRTS fraction. We assumed an order-and-ship time of 2 weeks. The average depot delay is unknown, but it will tend to be longer if the depot repair time is longer. As an arbitrary – but reasonable – procedure, we assumed that the depot delay would be .3 times the depot repair time. (We also used .1 with qualitatively similar results.)

TABLE 2-4

DATA

Source:	D041	
# Items:	560	
System:	C-5 nonengine, first indenture	
Elements:	1.	Worldwide base demand by item by quarter
	2.	Unit cost, NRTS value, average base and depot repair times by item
History:	12 quarters	
Predict:	4 quarters	

The prediction process, summarized in Table 2-5, consists of taking the 12 historical quarters of demand data and estimating the mean and VMR of demand for each item. The mean demand over the repair time and the VMR are used to estimate the two parameters of a negative binomial distribution of demand. This demand distribution is used to calculate the EBOs as a function of the stock level for each item. Then these backorder functions are used with unit cost to marginally allocate a fixed investment optimally across the 560 items. The result is a set of stock levels for each technique and an overall predicted availability. In the case of the Holt second-order smoothing that predicts trend, stock levels from the marginal allocation will be different in each predicted quarter.

TABLE 2-5

PREDICTION PROCESS

Input
1. Demand data by item for 12 quarters
2. NRTS and average repair time by item
3. Budget to allocate across items
4. Specification of demand prediction techniques
Process
1. Calculate EBOs as a function of stock level for each prediction technique and item
2. Use marginal analysis to allocate investment across items to maximize the predicted availability for the budget specified
Output by prediction technique
1. Stock level for each item
2. Predicted availability

We next evaluated the prediction techniques as summarized in Table 2-6. The inputs for the evaluation are the actual demands during the last 4 quarters, not used for prediction, and the stock levels by item. Unfortunately, we do not know the day on which each demand occurred, only the total quarterly demand. We therefore use a random number generator to draw the day during the quarter for each demand. On the basis of the item data on NRTS rate and repair times, we compute the day on which repair of the item will be completed. (The average repair time for the item is used, not a draw from a probability distribution with that mean.) The same sequence of demands and repair times is used for all techniques.

The output of this activity is an achieved availability for each technique. The availability is computed daily and averaged for each of the 4 quarters and for the entire year. Availability with cannibalization – consolidation of shortages onto the smallest number of aircraft – is also computed.

TABLE 2-6

EVALUATION PROCESS

Input

1. Total demand by item for each of 4 prediction quarters
2. Item stock levels by technique (and quarter when the technique estimates the trend)

Process

1. Draw from a uniform distribution the day (during the quarter) on which each demand occurs
2. Using the item's average repair time, determine the day that each repair is completed

Output

Average achieved availability by technique

CHAPTER 3

RESULTS OF THE EXPERIMENT

Detailed results are reported in the appendices. Here we display two important, general results that have been confirmed in all of our work on demand prediction. We term them "Fundamental Truths of Demand Prediction."

Finding #1: Demand in any period is more highly correlated with recent demand than with earlier demand.

The supporting evidence is to be found in Table 3-1. The first two columns are taken from Sherbrooke [2]. In that study, we computed the correlation between demand in quarter A with demand in quarter B for a group of items drawn from a stratified random sample. For 16 quarters of data, the quarters are separated by 1 quarter in 15 correlations, by 2 quarters in 14 correlations, etc. The first column of correlations shows that with 1,027 recoverable items selected at random, correlations decline smoothly from .966 to .845, as the number of quarters separating the quarters analyzed increases from 1 to 15.

The specific numbers are not important; they depend on the scatter in demand rates across items. The demand in each of 2 quarters across a group of items will appear to be more highly correlated when the item demand rates are scattered more widely. Thus, if we exclude the 28 items for which there were more than 1,000 demands in the first 8 quarters and compute the correlations for the remaining 999 items, the correlations fall from .924 to .454, as the number of quarters separating the quarters analyzed increases from 1 to 15.

The result is similar with items belonging to a single weapon system. The correlations in demand for recoverable items in the A-10 airframe and the F-16 engine/airframe are shown in the last two columns of Table 3-1. Though the correlations of the A-10 do not decrease uniformly as the number of quarters apart increases, the general trend is downward. Though flying hours for both the A-10 and F-16 increase over the 16 quarters, the correlation coefficient is not affected; that is, the slope of the relationship is changed but not the distances from the regression

line. Correlations based on demand per flying hour (see Appendix B) confirm these results.

TABLE 3-1

FUNDAMENTAL TRUTH #1 OF DEMAND PREDICTION

Number of quarters apart	1,027 items	999 items	480 items (A-10)	720 items (F-16)
1	.966	.924	.972	.966
2	.956	.904	.953	.944
3	.949	.886	.948	.939
4	.938	.869	.941	.935
5	.930	.833	.935	.919
6	.914	.807	.931	.899
7	.910	.791	.923	.888
8	.901	.752	.921	.887
9	.902	.718	.912	.862
10	.887	.662	.893	.836
11	.881	.634	.917	.834
12	.880	.594	.944	.824
13	.856	.523	.937	.811
14	.851	.472	.932	.780
15	.845	454	.921	.740

We confirmed these results using data other than quarterly data summed over all bases for a weapon system, as provided by D041. The day on which each demand for each item occurred was obtained for a single air base – England Air Force Base, Mississippi – and a single weapon system, the A-10. These data, aggregated into demand for 2-week periods, are shown in Table B-4 of Appendix B. It turns out that the correlational pattern is similar, even for shorter periods and an individual air base.

One problem with the correlations in Table 3-1 is the impossibility of determining whether the behavior observed applies to all items or to only a few. Correlations computed over time for individual items in Appendix B show that, for at least 25 percent of the items, correlations are positive and significant when data are drawn from adjoining periods.

The implication is that demand prediction techniques should allocate more weight to more recent data, because mean demand rates change over time. As we have seen, that is why the most successful power curve expressions for the VMR are based on the annual mean, not the mean over the repair time. Exponential smoothing is an example of a demand prediction technique in which more recent data are weighted more heavily.

Finding #2: Both variance and mean of demand must be estimated.

Table 3-2 shows the results of assuming Poisson demand where the variance equals the mean (VMR = 1). With an $80 million budget, predicted availability is .986, but achieved availability is only .566. Furthermore, that .566 availability is far below the availability of .828 that we could achieve by predicting the variance to mean from a power curve relation based on the mean. With that power curve relation, an availability of about .566 could be achieved with an investment of only $63 million, a saving of about 20 percent in investment. Results are similar when the budget amounts to $100 million. More detail is provided in Appendix A.

TABLE 3-2

FUNDAMENTAL TRUTH #2 OF DEMAND PREDICTION

Example	Predicted availability	Achieved availability
$80M budget		
VMR = 1	.986	.566
$VMR = 1 + .14M^{.5}$	.771	.828
$100M budget		
VMR = 1	.999	622
$VMR = 1 + .14M^{.5}$	.911	913

We have reached seven findings that – though less fundamental – have proved consistently true in all of our works so far:

1. *Exponential smoothing is the best technique for predicting mean demand.* The best value for the smoothing constant, when applied to quarterly data, appears to be about .4 (values from .3 to .5 give similar results). In the earlier AFLC study, Sherbrooke [2], exponential smoothing with a constant of .4 produced a 12-percent reduction in absolute error and a 30-percent reduction in squared error when compared with an 8-quarter moving average, the current procedure. In the present study, exponential smoothing and the 8-quarter moving average achieve about the same availability with a $100 million budget; with an $80 million budget, exponential smoothing achieves .83 availability, as compared with an achieved availability of .69 with an 8-quarter moving average. Appendix A includes more extensive details.

2. *When demand per program element (e.g., flying hours) is more stable over a base period than demand itself, it should be used in predictions.* Often, the program element is not in the D041 record or is zero for some quarters with positive demand, or has apparent errors that lead to a less stable data series. For example, of 933 items on the F-16, there are 774 for which program element data can be used, but only 511 for which demand per program element is more stable. For the other 422 items, demand per quarter is more stable and should be used. This question is addressed in detail in Appendices B and D.

3. *Data should be screened for outliers.* The best procedure is to identify probable data errors and bring them to the attention of the item manager. In some cases, it may be necessary not only to detect probable errors but also to make a best guess as to the correct value. A good correction procedure that improves predictions for a few items in every weapon system and never degrades the predictions is the following: Find the quarter with the greatest demand and, if that value is more than 5 times as large as the next highest demand and greater than 10 demands, replace that value by the average over the remaining 11 quarters. The only exception: If the largest value is in the last quarter, do not use the screen. Of course, the choices of 5 times and 10 demands are arbitrary, but a single quarter with a very large value is suspicious, as either a data error or a one-time special requirement.

   This screening procedure prevents the prediction from being overly sensitive to one very large (and probably erroneous) data point. Conversely, we want to prevent the prediction from being confused by an absurdly low data value. For example, exponential smoothing is most sensitive to the last data point. With the recommended smoothing constant of .4, 40 percent of the demand prediction weight comes from the

last data point. Suppose that every quarter of demand history has a positive program element and more than 100 demands. The one exception is that the data record for the last quarter shows a demand of zero (but a positive program element). Since underprediction of a very high-demand item can lead to severe degradation of the system, it makes sense to replace the zero with something like the previous data point or the average of several previous data points.

In fact, there are two such items in the F-16 data set (stock numbers 2840011253855 and 2840011253856). If such a screening procedure is not used, availability is nearly zero for all prediction techniques with a 2-year planning horizon. Note that this procedure is recommended only when the last demand value is zero, previous demand values have been large, and the program element is positive. By contrast, zero-demand values in earlier quarters are more likely to be accurate (there has been more time to correct the data record), and they have less effect on the prediction.

4. *Techniques for predicting the trend were unsuccessful.* This is a little surprising. We have ample evidence that demand rates change over time, but we cannot predict the trend of this change. As shown in Table A-2 of Appendix A, the Holt second-order exponential smoothing techniques are among the worst (availability of .693 versus availability of .828 from the recommended technique), and the error increases as we move further into the future. Of course, this does not *prove* the impossibility of predicting trend. All we can say is that we have been unable to find a procedure that improves the predictions by using the trend. A simpler problem is to predict not the size of the trend but the direction. Some unsuccessful attempts to do this are reported in Appendix C.

   At this point, there is no evidence that combination techniques improve predictive capability. In the only combination we used (see Appendix A), results for the $100 million target in Table A-3 were improved slightly, but the results for the $80 million target in Table A-2 were not. The matter should be explored further.

5. *Bayesian techniques are fairly good, but not the best available.* The objective Bayes procedure assumes that before any data on an individual item are processed, the probability distribution for demand is the same for every item. We did make one alteration in the objective Bayes procedure: For any item with extremely heavy demand (more than 1,200 demands in the first 12 quarters), the Bayesian procedure was not used, because it has a tendency to pull down the posterior demand mean to an unreasonably low value.

   The Bayesian techniques yielded the highest achieved availability for a $100 million target for the C-5 airframe (see Table A-3 in Appendix A) and high availabilities for an $80 million target (see Table A-2); they did less

well on the A-10 airframe. But they were not deemed the best for two reasons: First, the predicted availabilities were significantly higher than the availabilities actually achieved in all cases. Second, the Bayesian procedure is significantly more complicated; it requires estimation of a prior distribution by combining data on all items and a separate Bayesian inference for each item in each period with historical demand.

Since the mean tends to drift with time and we are unable to predict the trend, our best prediction of mean demand for an item is the same, regardless of how far ahead we are predicting. This implies our sixth finding.

6. *The estimate of variance should increase as the period being predicted advances into the future.* This is the subject of Appendix D, where VMRs are developed for longer prediction periods. From a theoretical perspective, this implies that a stationary compound Poisson process – used in much early work – is not a good representation of the physics. Our view is that we have a Poisson process, but the mean is changing over time. To compute the number of demands during a given period, we need a two-parameter, discrete probability distribution, with a variance that may exceed the mean. For this purpose, a negative binomial is a convenient choice.

7. *Different values of the exponential smoothing constant, depending on the level of mean demand, do not improve performance.* There was some suspicion that prediction for very low-demand items could be improved by incorporation of a longer history, equivalent to a smaller constant in the exponential smoothing. In our research, however (described in Appendix E), we found no empirical support for such a procedure.

CHAPTER 4

CONCLUSIONS

The major conclusions are:

1. Demand prediction techniques should give more weight to recent data, because mean demand tends to drift with time.

2. Exponential smoothing is consistently the best technique of those tested for estimating mean demand. With quarterly data, a smoothing constant of about .4 appears best.

3. Use of Poisson or a constant VMR assumption leads to poor allocations of investment, because system availability achieved during the prediction period is low. Across the system studies, a "good" choice for VMR as a function of the annual mean, M, is:

   $$VMR = 1 + .14M^{.5}$$

   For a fixed investment of $80 million on the C-5 airframe, the Poisson assumption leads to an achieved availability of .566; the formula above leads to .828 for the next year. Alternatively, the same availability could be achieved with 20 percent less investment and the VMR formula above. A slightly different formula for VMR is recommended if the prediction period is 2 years instead of one:

   $$VMR = 1 + .35M^{.55}$$

   Note that the independent variable, M, is the annual mean, rather than the mean over the repair/resupply time as used by AFLC. It is the drift in mean demand over the prediction period that is important.

4. When program element data, such as flying hours, are available and demand per program element is more stable, they should be used for prediction. If demand per quarter is more stable over the base period, that should be used, instead. In our analyses, slightly more than half the items were in the former group. The same prediction technique is recommended for both groups of items, but the choice of technique is more critical for the former group.

5. Screening techniques should be used to eliminate outliers. This includes cases where there is one very large demand, as well as cases in which demands have been very high and a zero demand is recorded for the last period. Specific procedures are suggested in Chapter 3.

The findings below are less definitive than the conclusions, because they depend on the techniques used in this study. It is possible that other researchers may devise new techniques that will alter one or more of these findings:

1. Techniques for predicting trend were unsuccessful. Since mean demand drifts with time, this implies that variance increases as the period being predicted moves into the future or becomes longer.

2. Combinations of techniques did not improve predictions. An example of a combination technique is a VMR that is the average of a power curve prediction (Conclusion 3) and a sample estimate based on historical data for the item.

3. Bayesian techniques used in this study were good but not best. The achieved availabilities were fairly high in most cases, but the predicted availabilities were almost always too high.

4. A different exponential smoothing constant for low-demand items did not improve predictions. There had been some suspicion that a lower exponential smoothing constant, equivalent to a longer history period, might improve predictions for very low-demand items.

These conclusions and findings appear to hold consistently across the C-5, A-10, and F-16 weapon systems as represented in 16 quarters of D041 data. Further support was found in an analysis of transaction data from a single A-10 air base – England Air Force Base – over a 2-year period. Data has been analyzed, both with and without program element information. Predictions have been made for both 1- and 2-year periods. We believe this has been one of the most comprehensive demand prediction studies undertaken for the Air Force in recent years.

Some words of caution are in order. There are a few items with very large and highly variable demand. System availability is critically influenced by how well the prediction technique performs on those items. Unfortunately, there is no way around this fact of life, which seems to be true of most weapon systems. This is not a defect in the evaluation measure; rather, it is related to the physics of our problem. The practical implications are that the technique for the VMR that is "best" for one weapon system is not likely to be "best" for all others, principally because of the behavior of a few items. However, we have found techniques that appear to do a good job across weapon systems and to be substantially better than techniques now in use.

Another point of caution is that a number of items show no demand over the base period. Having no basis for picking one prediction technique over another for these items, we have excluded them from predictions. For 2-year predictions, the number of these items in our data base increases, because the base period shrinks from 12 quarters to 8.

There are two implications: First, it is desirable to retain data history longer to improve detection of items whose "true" mean demand is not zero. Second, it may be necessary to estimate some positive demand for items with no observed demand (e.g., using a Bayesian procedure, as in Feeney and Sherbrooke [3]. If this is not done, the resulting value for weapon system availability is likely to be unsatisfactory. Prediction of demand for items that show no past demand is outside the scope of this report.

We have attempted to understand the "physics" of the demand process before comparing different techniques. This includes the statistical work that describes the drift in mean demand rate over time. If our understanding of the "physics" is good, the results should have wider applicability. However, this is not the final word on demand prediction.

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APPENDIX A

DETAILS OF DEMAND PREDICTION

INTRODUCTION

The objective in this appendix is to provide more detailed information about the demand prediction techniques used and the results of the experiment. For specified budget levels, predicted and achieved availabilities are shown for each technique on the C-5 airframe and A-10 airframe. The technique that yielded the best results was also the best in some preliminary calculations concerning the F-16 engine/airframe.

The major conclusion of relevance to this report is that a relationship of the form:

$$VMR = 1 + .14M^{.5} \qquad \text{[Eq. A-1]}$$

provides the "best" estimate of variance-to-mean ratio (VMR) for an item over the next year, based on an estimate of its annual mean, M. Furthermore, the "best" estimate of annual mean demand from quarterly data was obtained with exponential smoothing and a smoothing constant of .4. Additional evidence for this finding is to be found in Sherbrooke [2].

The word "best" has been enclosed in quotes, because this is an empirical finding and not the result of an optimization. It is possible that other candidate techniques could improve upon the procedures we recommend for estimating means and VMRs. This is even more likely with different data sets, particularly if data is not quarterly or if predictions are desired for periods substantially longer or shorter than a year. In Appendix D, we show that, for demand per program element on the F-16, it is possible to find a somewhat better prediction relationship for VMR than Equation A-1; for a 2-year prediction period, too, there is a better prediction relationship. Nevertheless, Equation A-1 represents a substantial improvement over techniques now in use.

DEMAND PREDICTION TECHNIQUES

We selected 17 candidate techniques that had shown promise in earlier studies. By a "technique," we mean a combination of a procedure for estimating the annual mean and a procedure for estimating the VMR. For example, the first four techniques in Table A-1 follow the same "objective" Bayesian procedure to estimate the VMR but different procedures to estimate the mean itself. An exponential smoothing procedure with a constant of .3 weights the most recent quarter by .3 and the previous estimate of the mean by .7. Repeated application yields these results: a weight of .3 for the latest quarter, a weight of .21 (.3 × .7) for the previous quarter, a weight of .147 (.21 × .7) for the previous quarter, and so on.

TABLE A-1

DEMAND PREDICTION TECHNIQUES

Technique	VMR
1. First order exponential smoothing using .3	Bayes
2. First order exponential smoothing using .4	Bayes
3. Last quarter (naive)	Bayes
4. 8-quarter moving average	Bayes
5. First order exponential smoothing using .4	1
6. First order exponential smoothing using .4	3
7. First order exponential smoothing using .4	$1 + .14M^{.58}$
8. 8-quarter moving average	$1 + .14M^{.58}$
9. First order exponential smoothing using .4	$1 + .216M^{.69}$
10. First order exponential smoothing using .4	$1 + .10M^{.58}$
11. First order exponential smoothing using .4	$1 + .14M^{.5}$
12. First order exponential smoothing using .4	$1 + .8R$
13. First order exponential smoothing using .4	$1 + 1.8R^{.58}$
14. First order exponential smoothing using .4	$2 + 1.8R^{.58}$
15. First order exponential smoothing using .4	From item data
16. First order exponential smoothing using .4	Average of Techniques 7 and 15
17. Holt linear exponential smoothing with .4 and .5	From item data

In the Bayesian procedure, the mean annual demand for any item in the group of items on a weapon system is assumed to have the same gamma prior distribution. The observed demand for all items during a quarter for all items is used to estimate the two parameters of the gamma prior by matching the first two moments of the distributions. Then, for a specific item, its demand is combined with the Bayesian prior distribution to calculate the posterior distribution of demand for that item. The mean and variance of that item posterior distribution are used as the two parameters of a negative binomial demand distribution to calculate the expected backorders (EBOs) for the item. This calculation is performed for each quarter independently, and the EBOs are combined across quarters by use of the weights from exponential smoothing or the moving average. This "objective" Bayesian procedure was used successfully in the original tests of the base stockage model, the forerunner of METRIC, and is described in Feeney and Sherbrooke [3]. The detailed equations are not included here, because the Bayesian procedure is not recommended, for the reasons described below.

One departure from this procedure is used for items with more than 1,200 demands annually during the first 12 quarters of demand history. For the 39 C-5 items with this property, the Bayesian procedure underestimates significantly the true mean demand (because it combines the information on all 560 items). For these items, we apply Technique 11 – the same technique recommended in Equation A-1.

Technique 5 is the constant, Poisson assumption; Technique 6 is a constant VMR of 3. Techniques 7 through 11 are variations on the procedures obtained by nonlinear estimation applied to Air Force Logistics Command (AFLC) data in Sherbrooke [2]. Techniques 12 through 14 are based on the repair/resupply time estimate of mean demand, R. Technique 15 estimates the VMR for the item from the 12 quarters of demand history on the item. Technique 16 applies the results of recent forecasting literature, where the suggestion is made that forecasts derived from combinations of techniques often outperform the individual techniques.

Technique 17 is the only one that attempts to predict trend in the mean demand. It combines exponential smoothing with a second-trend parameter and is described in Makridakis and Hibon [4]. To prevent extreme predictions, we limited the rate of increase or decrease per quarter to 15 percent of the mean demand

predicted from simple exponential smoothing with a constant of .4. The equations are not presented here because the results, as described below, were extremely poor.

DEMAND PREDICTION RESULTS

There are two primary considerations in evaluating the demand prediction techniques. The most important consideration is to obtain a high *achieved* availability during the prediction year. A less important but desirable property is to have a *predicted* availability that is fairly close to the *achieved* availability.

Our choice is Technique 11, marked with asterisks in Tables A-2 and A-3, because it has the highest *achieved* availability for a budget of $80 million and the fourth highest availability for a budget of $100 million. The three Bayesian techniques that finish ahead of Technique 11 in Table A-3 are overoptimistic; their *predicted* availabilities always exceed the *achieved*. Technique 11 produces *predicted* availabilities that are reasonably close to the *achieved* values. The Bayesian techniques have the additional disadvantages of being significantly more complex and unsuitable in an initial support planning context. The reason is that they require several quarters of past demand data to estimate VMR; the other techniques require only an estimate of the mean.

A few comments should be made about the other techniques. Technique 5, the Poisson assumption, yields especially poor results particularly as we move to quarter 4; Technique 6, with a constant VMR of 3, produces better though similar results. Not surprisingly, Techniques 7 through 11, as a group produce similar results. Note that the 8-quarter moving average – Techniques 4 and 8 – is inferior to exponential smoothing techniques with the same VMR procedure. It is a little surprising that Technique 9 did not outperform Technique 11, because nonlinear estimation techniques were used to estimate the best relationship for the C-5 from its own data.

Techniques 12 through 14 use a VMR based on the estimate of demand over the repair/resupply time. The poor performance of these techniques was a little hard to understand at first. Since the mean repair/resupply times vary by item from 6 to 57 days, the values of item mean repair time demand, R, are much smaller than the

item annual demand, M. Accordingly, larger coefficients are needed for comparable variability. However, it appears that these techniques are inferior to Technique 11, because it is not the variability over the repair/resupply time that is important, but the drift in the mean demand rate over the year.

TABLE A-2

ESTIMATED AVAILABILITY OF C-5 AIRFRAMES: $80 MILLION BUDGET

Technique	Cost ($ million)	Availability					
		Achieved annual	Predicted annual	Achieved by quarter			
				1	2	3	4
1	80.08	.812	.856	.827	.856	.851	.714
2	80.07	.825	.846	.853	.874	.858	.715
3	80.00	.701	.838	.853	.678	.698	.576
4	80.06	.686	.891	.687	.704	.723	.630
5	80.00	.566	.986	.849	.765	.631	.020
6	80.18	.678	.758	.870	.850	.833	.160
7	80.23	.810	.641	.856	.841	.851	.690
8	80.00	.796	.609	.826	.818	.871	.669
9	80.13	.746	.419	.742	.781	.816	.645
10	80.05	.822	.740	.886	.842	.848	.713
11	80.14	*.828*	.771	.891	.852	851	.719
12	80.01	.752	.731	.743	.790	.828	.647
13	80.00	.756	.724	.752	.791	.828	.652
14	80.01	.710	677	.698	.744	.780	.618
15	80.03	.776	.639	.789	.810	.848	.658
16	80.02	.795	.606	.812	834	869	.667
17	80.01	.693	.707	.737	.732	758	.543

TABLE A-3

ESTIMATED AVAILABILITY OF C-5 AIRFRAMES: $100 MILLION BUDGET

Technique	Cost ($ million)	Availability					
		Achieved annual	Predicted annual	Achieved by quarter			
				1	2	3	4
1	100.19	.925	.946	.981	.974	.957	.787
2	100.05	.917	.943	.971	.965	.946	.787
3	100.01	.790	.952	.926	.775	.771	.687
4	100.07	.924	.958	.945	.976	.962	.813
5	100.07	.622	.999	.919	.858	.689	.023
6	100.02	.774	.893	.964	.940	.924	.267
7	100.00	.905	.820	.952	.930	.928	.812
8	100.04	.905	.798	.951	.932	.958	.781
9	100.00	.889	.612	.929	.920	.940	.765
10	100.02	.913	.892	.964	.937	.925	.828
11	100.18	*.913*	.911	.968	.934	.919	.831
12	100.00	.888	.844	.923	.921	.944	.765
13	100.03	.896	.838	.934	.930	.949	.771
14	100.02	.878	.796	.917	.909	.935	.750
15	100.07	.893	.812	.930	.935	.947	.759
16	100.00	.906	.790	.948	.942	.958	.774
17	100.04	.831	.880	.866	.865	.892	703

Technique 15 reinforces the results of other studies that suggest the impracticality of estimating item VMRs from past history on the item, particularly since the item means are drifting over time. Technique 16 does not seem to be an improvement over its components, Techniques 7 and 15. Finally, the attempts to predict trend in the mean value from Technique 17 are consistent with results

reported in Sherbrooke [2]. Though demand means tend to drift over time, we have been unable to predict the direction of this drift for individual items.

Similar comparisons were made on the 480 items of the A-10 airframe. Ten of the more promising techniques from the 17 were chosen (see Table A-4).

TABLE A-4

ESTIMATED AVAILABILITY OF A-10 AIRFRAMES: $80 MILLION BUDGET

Technique	Cost ($ million)	Availability					
		Achieved annual	Predicted annual	Achieved by quarter			Achieved annual with cannibalization
				1	2	3	
1	80.00	.892	1.000	.726	.976	.973	.894
2	80.01	.927	1.000	.820	.975	.983	.929
3	80.05	.573	1.000	.406	.952	.361	.578
4	80.00	.870	1.000	.801	.852	.957	.906
5	80.07	.966	.979	.904	.999	.994	.966
8B	80.00	.703	.988	.500	.729	.880	.790
11	80.15	*.977*	.972	.998	963	.970	.980
13	80.02	.931	.617	.958	.945	.890	.961
15	80.01	.869	.735	.941	.845	.821	930
17	80.08	.764	.604	.914	.725	.653	915

Technique 8B is like the moving average Technique 8, except that the exponent of .5 is used, making the VMR expression identical with Technique 11. As in the C-5 case, Technique 11, which is exponential smoothing with a constant of .4 and the power curve relationship for VMR, is the best technique, as indicated by the asterisks in the table. It gives the highest achieved availability of .977 (only 3 quarters are shown); it yields the highest average availability of .980 in the last

column when full cannibalization – that is, consolidation of shortages on the fewest aircraft possible – is practiced.

Some of the major results in Table A-4 are noted here. Technique 8B (moving average) is far inferior to exponential smoothing with a constant of .4. (The other moving average, Technique 4, produces the worst results of all techniques.) The agreement between predicted and achieved availabilities is poor for all techniques except Technique 11, and the second best, Technique 6, which is a VMR of 3 on all items.

Table A-5 provides results for the 720 first-indenture items on the F-16 engine/airframe. The same 10 techniques were compared, and Technique 11 again came out best. It has a slightly lower achieved availability than Technique 13, but the predicted availability is in better agreement. We note that many of the predicted availabilities are too high, because the flying hours and demands increased substantially over the 16 quarters. For example, the demand rate during the last 4 quarters was about 41 percent greater than during the first 12 quarters. However, excellent availability was achieved with Technique 11, when this was not taken into account (except in the sense that exponential smoothing weights recent data more heavily in estimating the mean demand).

Some other observations concerning Table A-5 are noted here. The three Bayesian techniques (1, 2, and 4) and the Poisson technique (5) produced poor achieved availabilities. The best VMR relationship used in Technique 11 was also used in Technique 8B. The former employed exponential smoothing with a constant of .4; the latter used an 8-quarter moving average with far inferior results.

In the F-16 case, we looked at the items that were primarily responsible for the degradation in each technique. The Bayesian techniques and the Poisson did badly on five or six items that showed a rapid increase in usage over the 12-quarter base period. The best VMR performed much better on these items, particularly when it was used with the more responsive exponential smoothing instead of an 8-quarter moving average.

The F-16 differed from the C-5 and A-10 in that the demand (and the flying-hour program) increased substantially over the 16 quarters. It is likely that demand per flying hour will be more stable than demand itself. A more detailed analysis of the F-16 using program element data is presented in Appendix B.

TABLE A-5

ESTIMATED AVAILABILITY OF F-16 ENGINES/AIRFRAMES: $80 MILLION BUDGET

Technique	Cost ($ million)	Availability					
		Achieved annual	Predicted annual	Achieved by quarter			
				1	2	3	4
1	120.04	.022	1.000	.087	.000	.000	.001
2	120.01	.082	1.000	.327	.000	.000	.001
4	120.08	.000	1.000	.000	.000	.000	.000
5	120.01	.078	1.000	.310	.000	.000	.000
6	120.02	.376	.979	.889	.360	.245	.011
8B	120.01	.407	.990	.835	.343	.358	.094
11	120.00	*.905*	.980	.951	.867	957	.844
13	120.02	.906	.749	945	.863	.943	.874
15	120.00	.790	.695	.948	790	814	.609
17	120.07	.395	.590	.560	438	.340	.243

APPENDIX B

DEMAND PREDICTION USING PROGRAM ELEMENTS

INTRODUCTION

Here we compare two ways to predict demand and weapon-system availability – the present Air Force Logistics Command (AFLC) technique and the technique recommended in this report. By the current AFLC demand prediction technique, we use of an 8-quarter moving average to predict the mean and a variance-to-mean ratio (VMR) given by:

$$\text{VMR} = 1.1325R^{.3407} \qquad \text{[Eq. B-1]}$$

where R is the predicted mean demand over the repair/resupply time and VMR is constrained to be no less than 1 and no more than 5.

The technique we recommend (Technique 11 in Appendix A) is exponential smoothing with a smoothing constant of .4 to predict the mean and a VMR given by:

$$\text{VMR} = 1 + .14M^{.5} \qquad \text{[Eq. B-2]}$$

where M is the predicted annual mean demand and VMR is constrained to be no less than 1 and no more than 20.

RESULTS

A budget of $110 million was allocated across 920 first-indenture airframe and engine items of the F-16, using an optimal availability model and the two demand prediction techniques on 12 quarters of Recoverable Consumption Item Requirements (D041) data. The technique we recommend led to an achieved availability of .433 over the 4 quarters; the AFLC procedure led to only .201. This comparison utilizes program element information on items whenever the information is available; this is particularly important on such systems as the F-16, where demand changes dramatically.

With a budget of $180 million, our procedure led to an achieved availability of .704 versus .408 for the AFLC procedure. Backorders averaged three times as large under the AFLC procedure.

DESCRIPTION OF EXPERIMENT

The original sample of 1,214 items from the D041 data system for the F-16 engine/airframe was reduced by 281 items for which there was no demand during the first 12 quarters. Using data from the first 12 quarters only, we divided the remaining 933 items into two groups:

- *Group A*. The VMR for demand was smaller.
- *Group B*. The VMR for demand per program element was smaller.

Of the 933 items in Table B-1, demand per program element could be computed for only 774, because the program element (usually flying hours) was sometimes missing from the item data record. Of these items, demand per program element had a lower VMR over the first 12 quarters on 511 items; demand on the remaining were 422 items.

TABLE B-1

VMRs FOR ESTIMATORS A AND B

	Estimator A	Estimator B	Best A	Best B
Number of items	933	774	422	511
Average VMR	66.024	43.683	44 181	34.323

The average VMR for each group of items is shown at the bottom of Table B-1. Note that these VMRs are used only for separating the items between Group A and Group B, not for predicting demand. The reason for breaking the sample into two groups was to use demand or demand per program element, depending on stability; furthermore, we wanted to assess the prediction accuracy of our recommended procedure and the AFLC procedure for these two groups separately. The procedure

is similar to that used in Sherbrooke [2], where the computational formulas were derived.

In Table B-2, over the entire group of 933 items with some positive demand during the first 12 quarters, average demand per item increased from 22.0622 in quarter 1 to 50.9528 in quarter 16 (131-percent increase). When split into the two groups according to stability, average demand per item for Group A with no program element increased from 21.3483 in quarter 1 to 30.3175 in quarter 16 (42-percent increase); the average demand per program element for Group B increased from 27.0444/1,326 in quarter 1 to 70.1919/2,154 in quarter 16 (59-percent increase). Use of the program element does tend to improve stability over time.

The final number of items processed was reduced to a multiple of 20 for ease of processing, i.e., 420 items for Group A and 500 items for Group B. The budget of $110 million was divided in rough proportion to the number in each group, $50 million and $60 million, respectively. (When the budget was $180 million, the investment was split equally.)

Table B-3 shows the results for items in Group A and Table B-4 the results for Group B. The procedure was to use the first 12 quarters of D041 data to predict the mean and VMR ratio over the next 4 quarters, as described above. Then an optimal availability model was used to allocate investment across items. Actual demands during the next 4 quarters were to assess prediction accuracy. Briefly, the procedure was to determine probabilistically the day on which each demand occurred and the day on which each repair was completed. The availability was computed across the group of items on a daily basis and averaged over each quarter.

Achieved availability under no cannibalization and with cannibalization are shown in Tables B-3 and B-4. The average for the year is shown, as well as the values for each quarter. The average number of backorders is more than twice as large in each table where the AFLC procedure was used. In Table B-3, AFLC availability averages .532, compared with our .746; in Table B-4, AFLC availability averages .378 versus our .581. Multiplying availabilities to obtain the system values yields .201 for the AFLC procedure and .433 for our recommendation.

TABLE B-2

AVERAGE DEMAND/ITEM BY QUARTER FOR F-16

Quarter	Positive demand in 12 quarters	Estimator #1 best	Estimator #2 best	
		Average demand/ item by quarter	Average demand/ item by quarter	Flying hour/item by quarter
1	22.0622	21.3483	27.0444	1,326
2	25.0054	22.8839	31.6505	1,430
3	29.1629	23.8294	39.7060	1,567
4	27.9378	22.3389	38.4273	1,538
5	29.2765	23.7749	39.0995	1,552
6	30.4373	21.3152	43.7991	1,667
7	31.9625	20.5190	47.6622	1,850
8	35.7728	21.8175	54.4347	1,817
9	39.7717	27.0142	52.4633	1,756
10	45.0772	28.6422	60.6680	1,868
11	47.8617	29.2062	65.3131	1,969
12	46.8810	27.4360	64.9737	1,951
13	47.3655	29.1043	64.4646	2,011
14	49.5531	30.6682	67.2545	2,149
15	51.2776	30.1872	70.9152	2,242
16	50.9528	30.3175	70.1919	2,154

Each table shows some detail concerning items that cause backorders and lower availability within the group. We have printed the item repair/resupply time, the prediction of mean quarterly demand for each of the two techniques, the VMR for each technique, the stock level for each technique, the actual demands in the last 4 quarters, and the average backorders existing per day for each of the two techniques on the item. Only those items for which the sum of backorders by both techniques exceeds .5 are printed; the other items do not degrade availability.

TABLE B-3

GROUP A: DEMAND PER QUARTER/AVAILABILITY: 420 ITEMS

	Techniques			
	11	AFLC	11	AFLC
Cannibalization	No	No	Yes	Yes
Quarter				
1	0.837	0.637	0.909	0.816
2	0.678	0.450	0.843	0.788
3	0.807	0.582	0.904	0.800
4	0.622	0.459	0.802	0.795
Average	0.746	0.532	0.865	0.800

AVERAGE BACKORDERS BY ITEM BY PREDICTION TECHNIQUES

#	Resupply time	Predicted mean		Predicted VMR		Stock level		Demand in quarters 13 – 16				Expected backorders	
		11	AFLC	11	AFLC	11	AFLC	13	14	15	16	11	AFLC
49	9	81	46	4	2	16	11	113	113	82	84	0.2	1.5
50	10	77	44	3	2	15	11	136	122	86	86	0.6	2.7
51	15	122	123	4	3	30	34	126	115	133	141	0.6	0.1
80	19	1	1	1	1	2	2	0	2	2	2	0.4	0.4
91	30	2	2	1	1	5	4	12	15	6	6	0.2	0.4
94	42	21	8	2	2	28	16	32	32	32	27	0.0	0.6
107	22	8	13	2	2	8	11	9	48	21	15	1.0	0.4
120	9	15	8	2	1	7	4	33	30	4	70	0.7	2.0
135	19	5	5	2	1	6	6	19	8	33	5	0.3	0.3
136	18	57	60	3	3	24	26	72	102	104	83	0.6	0.3
142	22	31	26	3	2	21	19	57	70	67	62	0.1	0.4
183	18	2	1	[illegible]	1	3	2	33	10	2	2	1.0	1.3
198	24	374	302	6	5	202	168	332	349	596	491	0.0	0.6
202	19	0	0	[illegible]	1	3	2	24	0	0	0	0.4	0.7
205	14	4	3	2	1	3	3	2	23	11	4	0.3	0.3
213	13	279	162	6	3	75	47	320	368	360	332	0.0	[illegible]
223	30	43	47	3	3	41	46	22	135	23	15	1.2	0.5
224	26	122	96	4	4	81	69	158	240	158	137	0.3	1.4
232	19	69	62	3	3	21	22	59	76	84	[illegible]	1.2	0.9
233	17	20	[illegible]	2	2	11	10	[illegible]	125	62	66	1.5	[illegible]
250	16	124	131	4	3	52	53	160	213	245	365	3.9	[illegible]
284	20	20	7	2	[illegible]	20	9	57	75	56	93	1.6	[illegible]
363	18	74	36	3	2	25	15	172	165	145	72	6.8	[illegible]
416	35	[illegible]	[illegible]	[illegible]	[illegible]	4	1	10	2	2	5	[illegible]	[illegible]
Sum												[illegible]	[illegible]

TABLE B-4

GROUP B: DEMAND PER PROGRAM ELEMENT/AVAILABILITY: 500 ITEMS

	Techniques			
	11	AFLC	11	AFLC
Cannibalization	No	No	Yes	Yes
Quarter				
1	0.936	0.841	0.958	0.899
2	0.878	0.582	0.949	0.802
3	0.271	0.066	0.329	0.165
4	0.239	0.023	0.311	0.133
Average	0.581	0.378	0.637	0.500

AVERAGE BACKORDERS BY ITEM BY PREDICTION TECHNIQUES

#	Resupply time	Predicted mean		Predicted VMR		Stock level		Demand in quarters 13 – 16				Expected backorders	
		11	AFLC	11	AFLC	11	AFLC	13	14	15	16	11	AFLC
1	14	4	4	2	1	4	3	13	12	8	30	0.2	0.5
6	8	576	367	8	4	119	74	681	827	937	813	0.0	16.1
13	9	67	70	3	2	11	14	92	92	72	55	0.6	0.1
14	9	63	67	3	2	10	13	70	64	74	73	0.5	0.1
15	9	76	76	3	2	12	15	101	106	91	112	1.5	0.5
16	9	63	58	3	2	10	12	86	92	90	76	0.9	0.3
30	8	119	128	4	3	21	23	178	185	196	156	1.8	1.0
33	3	42	21	3	1	8	4	219	95	24	119	0.5	2.8
48	26	2	1	1	1	4	3	15	9	7	4	0.3	0.7
52	5	8	6	2	1	4	3	1	7	18	101	0.6	0.9
59	7	5	4	2	1	4	2	5	19	16	50	0.2	0.6
65	20	25	18	2	2	17	14	38	58	33	17	0.2	0.5
73	7	2,898	2,734	16	5	474	346	2,889	2,267	3,518	3,618	0.0	13.1
74	7	1,789	1,860	13	5	283	240	2,085	2,133	2,120	2,272	0.0	0.9
78	9	246	249	5	3	57	54	228	342	305	432	0.6	0.9
94	19	8	5	2	1	10	7	3	5	5	40	0.2	0.6
104	22	22	21	2	2	13	14	28	67	55	43	1.3	1.0
112	29	1,757	1,700	13	5	923	763	2,085	2,130	2,123	2,295	0.0	[illegible]
150	19	139	81	4	3	78	51	183	319	331	154	0.7	10.2
162	18	106	135	4	3	57	68	77	118	282	184	1.1	0.1
174	30	15	7	2	1	21	12	68	24	0	28	0.8	2.5
182	18	6	5	2	1	4	4	9	15	12	[illegible]	0.3	0.3
212	25	15	9	2	2	10	8	17	25	17	25	0.2	0.6
213	17	260	221	6	4	118	100	376	542	953	872	34.1	44.3
217	16	1,424	1,424	12	5	443	384	1,352	1,446	2,094	1,322	0.0	1.7
296	26	39	21	3	2	29	20	61	67	79	3	0.1	1.2
307	24	0	0	1	1	2	1	3	1	8	4	0.1	0.4
331	18	12	7	2	1	13	9	27	31	10	48	0.3	[illegible]
348	19	69	40	3	2	43	29	46	121	110	24	0.0	1.8
409	18	[illegible]	7	2	[illegible]	9	[illegible]	19	10	21	41	0.2	[illegible]
460	20	36	24	3	2	22	17	11	57	11	72	0.1	[illegible]
470	9	233	236	5	3	33	18	241	296	226	294	1.2	0.4
478	17	7	6	2	[illegible]	7	5	[illegible]	35	18	25	1.2	[illegible]
Sum												50.2	[illegible]

Let us now attempt to determine what accounts for the degradation in availability. In Table B-3 item #363 [national stock number (NSN) 6605011685185] is most important for both techniques. The item costs $89,000, and there was no program element in the data record. Our technique, as compared to the AFLC technique, estimated the mean to be twice as large and the VMR as 3 rather than 2. Consequently, our stock level was 25 rather than 15, cutting backorders by more that a factor of 2. There were several other items in Table B-3 where our technique reduced backorders substantially, mainly because of the more reactive estimate of the mean (e.g., #50, #120, #224, and #284). For other items, a combination of the mean and VMR seems to be responsible (e.g., #49 and #213). Note that the VMR for our recommended procedure exceeded the AFLC cutoff of 5 on only two items (#198 and #213). Our recommended procedure increases the backorders on some items. However, these tend to be items with fairly few backorders, and the maximum increase is only .6.

Turning to Table B-4, we find that item #213 (NSN 2840011433254), costing only $568, is most important in degrading both availabilities. Our technique predicts a larger mean and VMR, but backorders are reduced by only 25 percent (most of the backorders occur during the last 2 quarters). The AFLC technique has large backorders on three other items that are reduced substantially by our technique (e.g., item #6 due to mean and VMR, item #73 due primarily to the VMR, and item #150 due primarily to the mean). In this table, our technique leads to VMRs as high as 16, and a total of 6 items with VMRs in excess of 5. Happily our technique does not increase the backorders on any item by more than 1, a desirable feature.

One technical note should be added. The VMRs over the first 12 quarters (3 years) exceed 44 for demand (Group A) and 34 for demand per program element (Group B), as can be seen from the bottom of Table B-1. By contrast, the VMRs in our predictions are much smaller (exceeding 10 for only 4 items). The reason is that the VMR in the predictions is only over a year, and VMR increases with the length of the period.

Similar calculations were performed for the A-10 with comparable results. For example, on the 320 items where demand per program element was the better predictor the average availability with no cannibalization and a budget of $50 million was .943 for Technique 11 and .855 for the AFLC technique. The

expected backorders were 5.9 and 19.6, respectively. These values should be compared with Table B-4 for the F-16.

CORRELATIONS

In the main text, we have calculated the correlations between demand in 2 periods across items. It was noted there the correlation coefficient is not affected if demand is increasing over time uniformly across all items (the slope of the regression line is affected, but not the correlation, which is related to the distance of the data points from the regression line).

However, with a rapidly increasing program, such as that of the F-16, it is of interest to compute the correlations between demand per program element since the program element change may differ from item to item. When this is done for all 615 items on the F-16 with program element information in each of the 16 quarters, the results are shown in Table B-5. The correlations decrease less rapidly than those in the last column of Table 3-1 in Chapter 3, but the results are similar.

It is possible to compute correlations in a different way across periods for an item. The difference is that the means are now computed from an individual item, whereas in the previous correlations the means were computed across items for a specific period. With 16 observations, there are 15 intervals of length 1, 14 intervals of length 2, etc. We terminate the process with the 5 intervals of length 11, because the sample size becomes too small to test for statistical significance after that point.

Both types of correlation measure the degree of similarity between observations as the time interval between observations increases. The numerical values will be very different, near one for the first method and near zero for the second. The advantage of the first method is that the results for longer lags can be computed and compared.

TABLE B-5

CORRELATIONS

(Demand per program element: 615 F-16 items)

Number of quarters apart	Across items	Across periods by item		
		Correlation	Number of significant positive correlations	Number of significant negative correlations
1	.936	.201	151	11
2	.903	.085	91	18
3	.883	.049	225	20
4	.888	.029	64	26
5	.883	-.026	39	29
6	.869	-.030	40	33
7	.854	-.034	25	28
8	.849	.022	53	27
9	.845	.013	43	24
10	.829	-.019	33	28
11	.807	-.038	25	23
12	.810			
13	.826			
14	.825			
15	.749			

The advantage of the second method is that the results are not affected by the dispersion of mean demand levels across items. Statistical tests of significance can therefore be employed. Over the entire group of 615 items, the average correlation is significant at the 95 percent level for intervals of lengths 1 through 3. On an individual item basis, it is seen that many items have a significant positive correlation for intervals of lengths 1 through 4. After that point (a 1-year separation), the number of positive correlations that are significant tends to be only slightly larger than the number of significant negative correlations.

Table B-6 shows that analysis of the A-10 aircraft yields similar results. Over the entire group of 444 items, the average correlation is significant at the 95 percent

level for intervals of lengths 1 through 4; the number of items with significant positive correlation is also substantially greater than the number with significant negative correlation for intervals 1 through 4.

TABLE B-6

CORRELATIONS

(Demand per program element: 444 A-10 items)

Number of quarters apart	Across items	Across periods by item		
		Correlation	Number of significant positive correlations	Number of significant negative correlations
1	.921	.207	117	3
2	.910	.095	70	13
3	.897	.064	83	5
4	.886	.059	48	17
5	.869	.001	39	22
6	.872	-.048	19	26
7	.864	-.022	16	17
8	.849	.011	22	13
9	.851	.011	22	11
10	.844	-.038	18	16
11	850	-.056	9	18
12	.847			
13	.857			
14	.862			
15	.822			

All data analyzed in this report have been quarterly D041 data, where all base demands on a given weapon system have been aggregated. It is important to be sure that demand at an individual base is not fundamentally different from the sum of demand at all bases; that demand over shorter time periods does not behave differently. For this reason, we obtained the transaction data from a base for a 2-year period. The base was England Air Force Base, Mississippi, with A-10s, and the data covered the period from April 1982 through March 1984. The demands for

each item (XD-2) were aggregated in 2-week periods as the fundamental unit of analysis. The smallest meaningful period would have been a week, since we do not want the lighter flying schedule on weekends to bias the results. A 2-week period was selected so that demands during the period would be slightly larger; this gave us 52 periods for correlational analysis.

The results of similar correlational analysis on the 2-week demands at England Air Force Base are shown in Table B-7. Some major differences are noted from the previous correlations. The correlations decrease fairly uniformly (only the first 20 intervals are shown in the table, but the correlations decrease to .201 for the largest separation of 51 periods). However, the first value of .505 is much smaller than the first value in the other correlational analyses across items. The reason is that the average demands per period are much smaller and the variability in this number across items is much smaller (the average demand per item 2 weeks at England Air Force Base is about .2 percent, as compared with about 35 percent in each quarter across all F-16 bases).

The number of items whose correlations are positive and statistically significant when the periods are adjoining is only 95/741, or 12.8 percent, as compared with about 25 percent for the D041 data. Again, this is due to the low values of demand and the inability to obtain statistical significance. However, the qualitative behavior of the demand for 2-week periods is consistent with the D041 data, providing further support for our major conclusions.

TABLE B-7

CORRELATIONS – 2-WEEK PERIODS

(Demand per program element: 741 A-10 items)

Number of quarters apart	Across items	Across periods by item		
		Correlation	Number of significant positive correlations	Number of significant negative correlations
1	.505	.034	95	6
2	.478	.027	76	1
3	.465	.021	81	5
4	.443	.013	59	5
5	.445	.000	43	5
6	.449	.006	45	1
7	.427	–.003	39	3
8	.427	–.004	33	0
9	.413	–.007	26	2
10	.407	–.015	18	3
11	.395	–.021	22	6
12	.387	–.015	27	6
13	.384	–.007	36	7
14	.384	–.017	29	2
15	.389	–.015	22	10
16	.364	–.024	20	9
17	.373	–.020	29	8
18	.360	–.024	17	8
19	.346	–.024	12	8
20	.341	–.020	25	10

APPENDIX C

PREDICTING DIRECTION OF TREND

As noted in the main text, we have had little success in estimating trend values. A simpler problem addressed here is whether we can differentiate items that are likely to experience heavier demand in the future from those that are likely to have lighter demand. Predictions of trend direction based on demand (without the program element) for the A-10 (shown in Table C-1) were only slightly better than random. Initial results for the F-16 were encouraging, but the main reason was the increasing nature of the F-16 flying-hour program. When predictions were attempted on the basis of demand per program element, the results, as displayed in the table, were very poor.

The procedure we followed was to estimate the mean demand in the future by exponential smoothing with a constant of .4, the recommended technique from Appendix A. To construct a sign test, we then compared demands in the 12 base quarters with demands in the quarters that immediately precedes them. If the second quarter was larger than the first, +1 was added to a running total. If smaller, −1 was added. If they were equal, nothing was added. Then, following the same procedure, we compared the third quarter with the second, and the process continued until the eleventh and twelfth quarters were compared. The result was an integer statistic with values that could range from −11 to +11.

Our hypothesis was that the true mean over the last 4 quarters to be predicted was likely to exceed the exponential smoothing prediction when this statistic was positive; the more positive the statistic, the greater our confidence. In effect, we were hypothesizing that this statistic should be correlated with a positive trend, even though exponential smoothing gives greater weight to more recent data, in any case. The converse proposition is made with respect to negative values of the statistic.

The results for the A-10, using demand, and for the F-16, using demand per program element, are listed in Table C-1. Values of the statistic less than −4 were combined into the −4 category (since there were very few), and values greater than

+4 were combined into +4. Furthermore, results were combined for absolute values of the statistic, since we are likely to have similar confidence with a value of +4 or −4, though our inference is reversed. Results are shown cumulatively for other values of the statistic; e.g., 3 includes 4, on the assumption that if we draw the inference line at 3, we want to include 3 and any larger values.

TABLE C-1

PREDICTION OF TREND DIRECTION

Criterion value	A-10 demands on 489 items			
	4	3 – 4	2 – 4	1 – 4
Number correct	36	86	118	209
Number of items	66	160	233	407
Percentage correct	54.5	53.8	50.6	51.4
Criterion value	F-16 demand per program element on 615 items			
	4	3 – 4	2 – 4	1 – 4
Number correct	22	82	108	267
Number of items	47	174	229	516
Percentage correct	46.8	47.1	47.2	51.7

In the A-10 case, predictions that the statistic would equal or exceed 3 in absolute value proved accurate slightly more than 50 percent of the time, but these predictions pertain to only a third of the items.

The situation is the reverse for the F-16. Here the predictions for negative values when the criterion was applied to the F-16 were correct more than 61 percent of the time; that is, demand per program element was predicted to decline for 240 items, and 147 of these predictions proved to be right. This was balanced by the fact that, of predictions that demand per program element would rise for 276 items, only 120 were correct.

We tried weighting the more recent values of the statistic more heavily and also tried using the quantitative changes between quarters, rather than $+1$ or -1. The results were similar but slightly inferior.

APPENDIX D

BEHAVIOR OF VARIANCE-TO-MEAN RATIO (VMR) OVER TIME

VMR PARAMETERS THAT CHANGE BY QUARTER

In an earlier report on demand prediction for Air Force Logistics Command (AFLC), Sherbrooke [2], we estimated a formula for the VMR as a function of the exponentially smoothed prediction of the annual mean, M, and the number of quarters, Q, for which the VMR is desired:

$$\mathrm{VMR} = 1 + AM^{B} \qquad \text{[Eq. D-1]}$$

where $A = .141 + .0125Q$ and $B = .583 - .0045Q$. The estimation was based on values of Q from 4 to 8; values outside that range are extrapolations that should be used cautiously.

An alternative formulation that may be more useful is to derive expressions for A and B as a function of the number of quarters in the future. For example, the VMR over the next year for a specific item with mean, M, is not constant, as might be implied by Equation D-1. Our research shows that the value of A should increase and the value of B should decrease from quarter to quarter.

The problem is that, even when A and B are constants rather than functions of time, the optimal values can vary from one weapon system to another. Through most of this report, we have advocated values of $A = .14$ and $B = .5$. These values produce much better availabilities than the present AFLC techniques and a variety of alternatives and seem to perform well over the several systems tested. But the earlier research described above suggested that A and B should depend on the number of quarters being predicted; in particular, for demand over a year the values would be $A = .191$ and $B = .565$.

In the specific case of the F-16, the latter values yield availability of .780 versus .664 for $A = .14$ and $B = .5$ on the 500 items where demand per program element was more stable and availability of .865 versus .840 on the 420 items where demand was more stable. To test the way in which VMR should change with time, we set up

expressions for A and B such that when the number of quarters was 2.5 (halfway through the year), the values would agree with A = .191 and B = .565. The candidate expression tested and the resulting availabilities for the 500 items with demand per program element are shown in Table D-1.

TABLE D-1

AVAILABILITY FOR VARIOUS VALUES OF A AND B

A	B	Availability
.160 + .0125 Q	.576 - .0045 Q	.785
.129 + .025 Q	.5875 - .009 Q	.789
.129 + .025 Q	.61 - .018 Q	.778
.066 + .05 Q	.61 - .009 Q	.798
.066 + .05 Q	.5875 - .009 Q	.809

Note that these formulas – in contrast to those from Sherbrooke [2] – vary by quarter during the year; during the first quarter a value of Q = 1 is used; during the second, a value of Q = 2; during the third quarter, a value of Q = 3; and during the fourth quarter, a value of Q = 4. The predicted VMR on a given item increases from one quarter to the next.

These results suggest that availability can be improved by letting the values of A and B change by quarter. The impact seems to be fairly modest, though we have not performed an exhaustive search to determine the best relationships for A and B. Such a search has not been conducted, because even the average values of A = .191 and B = .565 have not been established as "best" for the F-16. The reason for the improvement in the average annual availability with time-dependent values for A and B is primarily the higher availabilities that prevail during the third and fourth quarters.

VMR PARAMETERS FOR A 2-YEAR PLANNING HORIZON

Throughout this report, we have focused on a planning horizon of 1 year for prediction. Procurement leadtimes are apt to be longer than 1 year, and the question arises whether to use a different formula for VMR when prediction over longer

periods is required. After all, we showed in the preceding section that the VMR should increase by quarter within a year, though the effect was slight.

Since we have 16 quarters of data, it is possible to use the first 8 quarters (instead of 12 quarters) as the base period and predict over the last 8 quarters, or 2 years. This is similar to the procurement leadtime on many items. Furthermore, the current Air Force procedure uses only 8 quarters in the moving average, and exponential smoothing with a weight of .4 gives negligible weight to data that are more than 8 quarters old.

The analysis reported in Appendix B was repeated for a 2-year prediction period. The AFLC technique of Equation B-1 was again compared by our recommended technique of Equation B-2 for a 1-year horizon. Eight other techniques with slightly different expressions for VMR were also compared. As before, the calculations were performed for the F-16 and A-10 with separate computations for the group of items where demand per program element was more stable. The best of these 10 techniques was:

$$VMR = 1 + .35M^{.55} \qquad \text{[Eq. D-2]}$$

This technique performed somewhat better than other techniques, but no claim of optimality can be made.

Only summary results are presented here. It should be noted that the number of items with zero demand is much higher than in Appendix B, because there is only an 8-quarter history period. For the same reason, the number of items for which demand per quarter is more stable and the number for which demand per program element is more stable differ from the figures in Appendix B.

Note that the budget allocation for a specific weapon system between the group of items best predicted by demand per quarter and the group by demand per program element is not optimal. In a real application, all items for a weapon system should be run at one time so that the same Lagrange multiplier is used. We have separated them here, for analytical purposes, to study the behavior of each technique on each group. An important conclusion that emerges here, as well as in Appendix B, is that the same technique should be used on both groups of items.

The middle part of Table D-2 shows the average availabilities achieved over the 2-year prediction period under the condition of no cannibalization; the lower part shows the availabilities with cannibalization, or consolidation of part shortages on the fewest end items.

Clearly, our recommended prediction – Technique 11 from Appendix B – is generally much better than the AFLC technique, and our new technique from Equation D-2 is better still for the 2-year prediction. This result is true, with or without cannibalization. The largest improvements are found in the group of items that are best predicted by demand per program element.

TABLE D-2

2-YEAR PREDICTIONS

	F-16		A-10	
	Demand per quarter	Demand per program element	Demand per quarter	Demand per program element
Number of items	340	380	200	260
Budget ($ million)	80	80	60	80
Technique	Achieved availability with no cannibalization			
	F-16		A-10	
	Demand per quarter	Demand per program element	Demand per quarter	Demand per program element
Eq. B-1 – AFLC	.564	.136	.367	.236
Eq. B-2 – 11	.578	.561	.470	.533
Eq. D-1 – New	.678	.729	.481	.622
Technique	Achieved availability with cannibalization			
	F-16		A-10	
	Demand per quarter	Demand per program element	Demand per quarter	Demand per program element
Eq. B-1 – AFLC	768	452	659	654
Eq. B-2 – 11	.755	795	713	779
Eq. D-1 – New	871	880	706	833

APPENDIX E

LOWER SMOOTHING CONSTANT FOR LOW-DEMAND ITEMS

There was some suspicion that predictions for very low-demand items could be improved by incorporation of a longer history, equivalent to a smaller constant in the exponential smoothing. Our procedure was to use a smoothing constant of .1 on any items for which demands numbered fewer than 10 demands in the first 12 quarters (typically about 20 percent of the items). Though the predicted availabilities were very slightly higher, the actual achieved availabilities were slightly higher in only one case and lower in seven. This is shown in Table E-1. It should be noted that the values of .1 and 10 demands are arbitrary. Different values may give somewhat different results.

In Table E-1, the achieved availabilities are generally higher than the predicted availabilities for the C-5 engine, lower for the A-10 and F-16. The reason is that the annual dollar value of demand for the C-5 engine decreased during the period being predicted to only 62.6 percent of its value in the base period, while the value increased 19.5 percent for the A-10 and increased 41.4 percent for the F-16. However, the allocation of investment appears to have been very good. Results for an 8-quarter moving average are shown at the highest budget level for each weapon system. Note that in two of the three cases, the moving average leads to severe degradation in achieved availability.

In summary, Technique 11 with a smoothing constant of .4 for all items appears to be best.

TABLE E-1

AVAILABILITIES WHEN DIFFERENT SMOOTHING CONSTANTS ARE USED

C-5 Engine				
Smoothing constant	4 for all items		1 for items with fewer than 10 demands	
Budget ($ million)	Predicted	Achieved	Predicted	Achieved
10	.614	.796	.615	.796
15	.803	.878	.805	.878
20	917	.955	.917	.956
25	972	.977	.972	.974
25	.975[a]	.978[a]		
A-10 Airframe				
Smoothing constant	4 for all items		1 for items with fewer than 10 demands	
Budget ($ million)	Predicted	Achieved	Predicted	Achieved
40	205	309	207	303
60	788	847	789	844
80	972	962	972	960
100	997	987	997	987
100	999[a]	601[a]		
F-16 Engine/Airframe				
Smoothing constant	4 for all items		1 for items with fewer than 10 demands	
Budget ($ million)	Predicted	Achieved	Predicted	Achieved
60	359	225	361	224
90	808	733	809	729
120	962	927	963	925
150	994	974	994	974
150	998[a]	392[a]		

[a] Indicates the result of an 8-quarter moving average to predict the mean rather than exponential smoothing

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Reparable spares of aircraft components constitute an important management item for the Air Force, amounting to a computed budget requirement of $4.077 billion in FY85. Allocation of this investment a cross items is critical to the readiness and sustainability of weapon systems. Proper allocation, in turn, depends on solving the statistical problem of estimating item demand rates and variances.

Using historical Air Force data, we have compared the performance of various estimating procedures, including the one used in the Air Force Recoverable Consumption Item Requirements (D041) System, which computes item Peacetime Operating Stock (POS) requirements. To be consistent with Air Force orientation toward weapon system management, aircraft availability, an aspect of readiness, served as the measure of performance.

The major conclusions were that the mean demand should be estimated using exponential smoothing and the variance-to-mean ratio as a power function of the mean demand. When compared to current AFLC policy, the proposed techniques showed a reduction in backorders of over 50 percent for the F-16 and A-10 weapon systems.

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